14. Estimation of Non-market Forest Benefits Using Choice Modelling

Jungho Suh

This module is concerned with some fundamental features and conditions of choice modelling applications to non-market valuation. Choice modelling is an advance on the contingent valuation method (CVM), and is creating strong interest among researchers, and has much potential for non-market valuation in multiple use forestry. To undertake a choice modelling application for estimating non-market values, potential practitioners need to understand the theoretical issues and practicalities involved in applying the technique. These include the statistical foundation of choice modelling, strict rules for the experimental design and ways of utilising the estimates. This module first outlines the characteristic features of choice modelling in terms of the method of evaluating resource use alternatives, compared with contingent ranking, contingent rating and CVM. Some basic assumptions and considerations needed in designing choice sets are then examined. Roles and rules of focus groups are next introduced. Some choice modelling applications made in forestry research are then briefly reviewed. Finally, ways of extrapolating welfare measures from a choice modelling application are reviewed. More complex statistical issues are explained in three appendices.

1. THE CHOICE SET FORMAT OF CHOICE MODELLING

Choice modelling originated from conjoint analysis, and is also a variation on contingent valuation. In comparison to CVM, conjoint analysis describes options by decomposing them into a number of attributes, and presents respondents with a choice between *j* available options ($j = 1, 2, \cdots, J$). This situation can be made quite realistic by mirroring actual market choice that may depend upon a number of attributes.

If the number of available options is too large, the full options are divided into several sets. Then, respondents are asked to rank, rate or choose their preferred combination from each set. Moreover, the number of sets can be increased to as many as each respondent can answer within a limited time. For this reason, it is said that one of the major advantages of conjoint analysis compared to CVM is that many options provide a large number of observations so that fewer respondents are required to yield results within acceptable confidence limits.

Conjoint techniques have been widely used in marketing studies dealing with market goods rather than non-market goods. Conjoint analysis is founded on the theory of consumer preference in an attempt to describe how consumers choose between similar products, for example, beers, coffees and soft drinks. Respondents are asked to rank or rate or choose from a set of multiple product profiles. Setting prices for the products was not necessarily the primary concern of conjoint analysis in marketing studies. In this sense, the fact that conjoint analysis was eventually developed to value non-market public goods can be dubbed a 'paradigm change' in the field of economic valuation.

The rationale of conjoint analysis applications for estimating environmental non-market values is that it is possible to estimate the amount that people are willing to pay to achieve a greater amount of one or more environmental attribute, given that the dollar cost is treated as one of the characteristics for a non-market good. In fact, the price factor does not represent an inherent attribute of a commodity under consideration. Rather, the price presents dollar costs that are traded off for proposed changes in attribute levels. This is why Mitchell and Carson (1989) classified conjoint analysis as a 'hypothetical and indirect' approach.

In contingent ranking, respondents rank three or more options from most to least preferred. In the contingent rating application, respondents are asked to rate each option separately on a given rating scale instead of ranking the options. For example, consider the case of a protected forest area as illustrated in Table 1, where z_k^j represents the *k*th attribute of the *j*th option and z_p^j is the price factor. The protected area is here defined as a combination of attributes, each of which may take various levels. If a respondent prefers the *j*th option $\{z_1^j, z_2^j, \cdots, z_k^j\}$ to the other options, a higher ranking or rating is assigned to the *j*th option. Compared to contingent ranking, contingent rating contains cardinal information. In choice-based conjoint analysis, respondents are asked only to choose their highest preference from among several options – for example the set of choices presented in Table 1. Carson *et al.* (1994) called this method 'choice modelling' to distinguish it from contingent ranking or rating. In some literature, the term 'environmental choice experiments' is used rather than choice modelling, especially by the Canadian group of practitioners.

It is notable that a dichotomous CVM question is the same as a binary choice modelling one except for the pricing format (Bennett and Carter 1993; Roe *et al*. 1996; Stevens *et al*. 2000). Consider a choice modelling question with only one alternative (two options), as in Table 2, where respondents are asked whether to accept the new option, comparing to the current status option. Note that one of z_k represents the WTP amount (z_p). It can be seen that the question is virtually identical to that of a dichotomous CVM where respondents are asked whether they would be willing to pay z_p for the same change in z_k.

Choice modelling has an advantage over contingent rating in the sense that the former is free of metric bias with which the latter is plagued. Metric bias occurs when a respondent values an amenity according to a different metric or scale than the one intended by the researcher (Mitchell and Carson 1989). This bias also relates to the problems of interpersonal comparison of cardinal measurement of utility (Morrison *et al*. 1996). Since individual rating scales in contingent rating applications reveal only relative value between the respondents, it is necessary to assume that rating scales being used are consistent across individuals (Rolfe and Bennett 1996). Similarly, contingent ranking suffers inconsistent ordinal measurement of utility across individuals.

2. ASSUMPTIONS AND CONSIDERATIONS IN THE EXPERIMENTAL DESIGN

Any type of market or non-market good can be described by a range of characteristics. In applications of choice modelling, a number of hypothetical profiles are created by combining distinct levels of attributes, which must represent a wide range of characteristics of the object being valued. The number of attributes and their levels determines the total number of distinct profiles. A full factorial design includes all combinations of the attribute levels, where every level of a given attribute is combined with all levels of every other attribute. In general, if there are *m* factors and *n* levels of each, n^m unique combinations can be made. If factor space S has *k* factors, S = $(z_1, z_2, \cdots, z_k)$, and each factor z_k has L_k possible levels, then S has $L_1 \times L_2 \times \cdots \times L_k$ possible combinations.

Question formats based on complete factorial design quickly become impractical due to the cost of administering the survey, not to speak of the respondents' confusion and fatigue, as the number of either factors or levels of the individual factors increases. Indeed, in many cases, a choice modelling researcher is simply unable to conduct a survey using a large number of profiles. Hence, the researcher is forced to adopt a fractional factorial design, where only some of the combinations of factor levels are included. In choice modelling practice, a selected fractional factorial design is again broken into a number of separate choice sets. Rolfe and Bennett (1996) noted that the number of choice sets should not be too onerous for a single respondent. They suggested that choice sets be divided into manageable blocks, with each block allocated to a sub-sample of respondents.

Table 1. A choice format with several scenarios with various levels of attributes

Option (j)	Attribute (z_k)				
	z_1	z_2	…	z_k	z_p
1	z_1^1	z_2^1	…	z_k^1	z_p^1
2	z_1^2	z_2^2	…	z_k^2	z_p^2
:	:	:	:	:	:
J	z_1^J	z_2^J	…	z_k^J	z_p^J

Table 2. A binary choice modelling question format

Option	Attribute (z_k)				
	z_1	z_2	…	z_k	z_p
Current situation	z_1^0	z_2^0	…	z_k^0	z_p^0
New option	z_1^1	z_2^1	…	z_k^1	z_p^1

Louviere (1988) warned that one must be cautious of fractional designs because a strictly additive utility function, known as the orthogonality assumption, underlies choice modelling. The orthogonality assumption means that choice modelling estimates only the main effect of each attribute on the overall utility, assuming that all interaction effects between attributes are zero. Thus, choice modelling questions should be designed to comply with the orthogonality assumption. Further explanation on the orthogonal experimental design is provided in Appendix A.

For designing a choice modelling questionnaire, a few other considerations are required. First, the number of choices available in a choice set should be manageable from the viewpoint of respondents. Hanley and Spash (1993) warned that a choice set with five or more choices for the contingent ranking method would make respondents confused and threaten the reliability of the information gained from the contingent ranking study. In choice modelling applications, the confusion would be less evident because respondents are not asked to rank the options in order of their preferences. Nevertheless, a large number of options in a choice set may cause the same problems. It is notable that the minimum number of options that should appear in each choice set is three.

Second, extreme care is called for regarding the levels and range of the payment variable. Lareau and Rae (1989, pp. 729–730) in an empirical study of the contingent ranking technique warned that “if prices are too low, respondents order options by focusing mainly on the environmental attributes, while if prices are too high, respondents order options according to the price attribute.” This warning is applicable to choice modelling studies. Respondents would choose an option by focusing mainly on the environmental attributes if prices are too low and by focusing on the financial attribute if prices are too high. By the same token, Rae (1983) called attention to the price range. Too small a range may result in underestimating the values of other attributes when a large number of respondents, who are willing to pay more than the maximum, exist. Similarly, too wide a price range with only a small number of price levels may effectively force a trade-off, but lessen the chance of obtaining precise estimates within the range.

Third, too many attributes cause respondents to state their preferences by 'indicator attributes'. The indicator attribute effect occurs when respondents face complicated combinations of attributes, and then use a single attribute to indicate what would happen to the other attributes (Morrison *et al*. 1997), rather than evaluating each option by weighing up the levels of each attribute. On the other hand, too few non-monetary attributes may generate payment vehicle bias and substantially offset the effects of de-emphasising the payment mode (Morrison *et al*. 1996). Payment vehicle bias occurs when the payment vehicle employed influences how an individual responds to questions about WTP.

Bennett (1999) stressed that the payment vehicle must be compulsory and have broad coverage so as to be relevant to all respondents, as used in Rolfe *et al*. (2000). The rationale for presenting the compulsory payment vehicle is that the use of a donation as a payment vehicle encourages strategic responses. Therefore, it is argued that respondents must be convinced that they will be called upon to actually pay the amount they agree to pay when they choose options from choice sets.

The compulsory payment vehicle is not always desirable in the sense that it may also cause strategic responses. Morrison (1999) stressed that if the payment scenario is not acceptable, people may simply refuse to be interviewed in protest against the payment vehicle, take the survey less seriously or ignore the amount of payment. That is, people may reject the notion that they should have to pay for hypothetical new improvements in the quality of natural resources because they have paid taxes for the environmental improvement, even though respondents obviously derive utility from the environmental improvement. Flatley and Bennett (1994) reported that Lockwood *et al*. (1993), in a pilot study of a CVM survey to value areas of Gippsland forest, found a strong anti-government sentiment emanating from publicity over the troubles being experienced by various state-controlled financial institutions. Consequently, the forest valuation study had to use contributions to an independent trust as the payment vehicle in order to avoid the public's sentiment against the imposition of new taxes influencing WTP bids.

3. ROLES AND RULES OF FOCUS GROUP SESSIONS

Focus group sessions are a commonly used tool in psychology and are often regarded as a crucial step in shaping the market strategy for products. Krueger (1988) defined a focus group meeting as a carefully planned discussion designed to obtain perceptions on a specific area of interest in a permissive, non-judgmental and non-threatening atmosphere. The meeting with a small group of people is initiated and guided by preferably an experienced facilitator. Leading a focus group may require the combined skills of an ethnographer, a survey researcher and a therapist. Morgan (1988) pointed out that the main advantage that focus groups offer is the opportunity to observe a large amount of interaction on a topic in a limited period of time. In comparison with directive interview that is dominated by the interviewer, members of a focus group are allowed to talk without setting boundaries or providing cues for potential response categories. The moderator is not supposed to take the lead, but is expected to allow the advantages of non-directive interviews that use open-ended questions. The facilitator's skilled control over focus groups is, therefore, a key to successful meetings.

Krueger (1988) and Bernard (1995) suggested that a focus group be characterised by homogeneity, but ideally composed of strangers who do not know each other and will likely not ever see each other again. Homogeneity is sought in terms of occupation, social class, educational level, age and family characteristics, so as to avoid some mixes of participants that do not work well because of limited understanding of other lifestyles and situations. For example, participants will be inhibited by those whom they perceive more experienced, knowledgeable or better educated. Krueger (1988), however, pointed out that sufficient variation among participants to allow for contrasting opinions is helpful to obtain the contrast and variation that spark lively discussions.

Rolfe and Bennett (1995) and Blamey

(1998) pointed out that focus group sessions are an integral part of stated preference methods, in which underlying theory of consumer behaviour is linked with psychology. Focus groups are routinely used in the developmental phase of CVM studies. Rolfe and Bennett (1995, p. 3) summarised the major roles of focus groups in an environmental valuation exercise. These are:

1. establishing the overall framework and characteristics of the good in question including the relationship to other goods and applicable institutional settings;
2. ascertaining the extent of knowledge that people have about particular goods, and the ways in which they value those goods;
3. identifying and describing the major attributes that people consider when valuing particular goods; and
4. establishing appropriate trade-offs or WTP amounts associated with changes in the particular goods.

Running focus groups is even more vital in choice modelling studies, given that a choice modelling questionnaire tends to be much more complex than a CVM questionnaire. Through focus groups, choice modelling practitioners can determine which attributes are relevant to participants and test whether the information presented is appropriate; whether the main issues are communicated effectively and whether participants understand the choice modelling process sufficiently to handle choice sets; and whether the upper and lower bounds for the levels of the financial attribute are adequate (Morrison *et al*. 1997).

Focus group participants are expected to reveal the beliefs and attitudes that they actually consider when making environmental decisions. For this reason, Rolfe and Bennett (1995) argued that focus group sessions have to be involved from the questionnaire design stage rather than from the testing stage. In practice, focus groups are often used for testing a draft questionnaire and designing the final questionnaire.

One and a half to two hours is reasonable to run a focus group meeting for stated preference studies (Morrison *et al*. 1997). Stewart and Shamdasani (1990) noted that taking part in a focus group is a time consuming activity for participants in practice. Spending two or more hours talking to a group of strangers is not likely to be viewed as an appealing prospect. This is more likely the case if one has worked all day. They noted that a variety of incentives may be used to encourage participation, and monetary incentives are commonly used to induce individuals to spend time in a focus group.

It is recommended that a focus group have five to 10 members plus a moderator (Rolfe and Bennett 1995; Morrison *et al*. 1997). The group size is determined by two factors: it must be small enough for everyone to have opportunity to share insights yet large enough to provide diversity of perceptions (Krueger 1988). Bernard (1995) pointed out that if a group is too small, the group can be dominated by one or two 'loudmouths', and if the number of group members is beyond 10, it becomes difficult to manage the group. Krueger (1988) mentioned that a focus group is typically composed of seven to 10 people, but the size can range from as few as four to as many as 12. He noted that small focus groups or mini-focus groups with four to six participants are becoming increasingly popular because the smaller groups are easier to recruit and host, and more comfortable for participants.

4. CHOICE MODELLING APPLICATIONS IN THE NATURAL ENVIRONMENT INCLUDING FORESTRY

There have been many choice modelling applications to recreation studies or environmental conservation research. Adamowicz *et al*. (1994) analysed the welfare impacts of changes in a set of attributes of recreational fishing sites. Hanley *et al*. (1998) focused on the identification and valuation of key attributes affecting forest choice by conservation-oriented recreational users and non-users. Recent choice modelling applications dealt with urban tourists' portfolio choices of destination and transportation components (Dellaert *et al*. 1997), the environmental values of water supply options of a river

(Blamey *et al*. 1999), improved wetland quality (Morrison *et al*. 1999) and choice of recreational theme parks (Kemperman *et al*. 2000). Examples of choice modelling applications to forestry studies include valuing international rainforests (Rolfe and Bennett 1996; Rolfe *et al*. 1997) and evaluating a tree clearing policy (Rolfe *et al*. 2000).

Rolfe and Bennett (1996) used choice modelling to estimate demand by Australians for rainforest conservation in overseas countries. This choice modelling study was undertaken in Brisbane in 1995. The key attributes that were used in the survey were location, rarity, effect on local people, potential for future visits, size and possession of special features. The location attribute was varied across six locations, while each of the other attributes varied across three levels. There were six options in each choice set. Each respondent was presented with nine choice sets. This study demonstrated how it is possible to derive estimates of value for overseas rainforests.

Rolfe *et al*. (2000) conducted a choice modelling experiment to estimate the values held by Brisbane residents for both environmental and social factors associated with tree clearing in the Desert Uplands region of central-western Queensland. The implication of changes to tree clearing regulations were described in terms of six attributes as presented in Table 3. Respondents were presented with a *status quo* option (Option A) and two options for increased preservation. A series of eight choice sets were presented to each respondent. This study found that Brisbane households hold substantial protection values for native vegetation in the Desert Uplands.

The choices made of interview are typically entered into a spreadsheet for subsequent processing. Suppose that a respondent chose Option 3 from the list in Table 3. With this choice observation, three records can be entered as presented in Table 4 on a typical spreadsheet such as Microsoft Excel. Choice modelling requires that the dataset be arranged with a line of data for each option. If choice modelling data are collected from 10 respondents, and each respondent is asked to tick eight different choice sets, 240 records are generated. In choice modelling applications, sample sizes are generally about 300. Staying with eight choice sets per respondent, this means that 7,200 records are obtained from a choice modelling survey.

The dataset can be analysed with a statistical package such as Limdep 7.0, a specialised program for the estimation of qualitative response models and limited dependent variable models.

Table 3. A practical example of choice set

Implications	Option A (current guidelines)	Option B	Option C
Levy on your income tax	None	$60	$20
Income lost to the region ($ M)	None	5	10
Jobs lost in the region	None	15	40
Number of endangered species lost to region	18	8	4
Reduction in population size of non-threatened species	80%	75%	45%
Loss in area of unique ecosystems	40%	15%	28%

Source: Rolfe *et al*. (2000, p. 12).

5. WELFARE MEASURES EXTRAPOLATED FROM CHOICE MODELLING ESTIMATES

Discrete choice models have historically been the main models used in choice modelling studies. What is meant by discrete choice models is that those models in which the dependent variable takes discrete values. The simplest of these models is the binary choice model in which the dependent variable *y* takes the value of 0 and 1 (Maddala 1983). An example of this is presented in Table 4: *y* is defined as 1 if the respondent chooses Option 1, *y* is defined as 0 if the respondent does not choose the option, and so forth.

Table 4. An example of choice modelling data entered on a spreadsheet

Record no.	Variable						Choice (*y*)
	Levy	Regional income	Jobs	Endangered species	Population size	Ecosystems	
1	0	0	0	18	80	40	0
2	60	5	15	8	75	15	0
3	20	10	40	4	45	28	1

For a choice set with *J* alternatives, an estimated discrete choice model can be expressed as:

$$L_j = \ln\left(\frac{P_j}{P_{j'}}\right) = V(z_k^j) = b_0 + b_1 z_1^j + \cdots + b_K\, z_K^j$$

$j = 1,2,\cdots,J$ (1)

where z_k^j refers to the *k*th attribute of the *j*th option, one of z_k represents the price, and b_k is the weight or coefficient associated with an independent variable z_k. Equation 1 indicates that the logarithm of probabilities that a particular choice will be made can be represented by the systematic component of utility of the *j*th option. This is assumed because choice modelling aims to yield the unbiased estimate of the main effects of those attributes on utility only (Adamowicz *et al.* 1994). The independence property that all the attributes must be independent of one another is the most important feature pertaining not only to choice modelling but to all types of conjoint analysis. Further details of the discrete choice model are presented in Appendix B.

The independence of irrelevant alternatives (IIA) is inherently assumed for logit models. The IIA assumption implies that the odds of choosing the *j*th option in relation to one of the other options must be constant regardless of whatever other options are present (Louviere and Woodworth 1983). Violations of the IIA property may occur in applications where options are close substitutes for one another. The property is also implausible when there exists heterogeneous tastes (Morrison *et al.* 1999). When the IIA property is invalid, parameter estimates from the relevant discrete choice model will be biased. The IIA assumption is a substantive restriction on the generality of the logit models. Thus, testing for presence of the IIA property is a standard empirical procedure in obtaining a valid empirical logit model. Appendix C provides commonly used methods of detecting the IIA violations.

The estimated parameters of a discrete choice model provide a basis to compute the trade-offs between dollars and environmental quality. Compared to CVM, a single choice modelling exercise can separately and simultaneously estimate the coefficients of all factors involved in choice sets. For example, the WTP to avoid each 1% reduction in non-threatened species can be obtained from the choice modelling analysis using the Rolfe *et al.* (2000) dataset. Consequently, compensating surpluses for numerous hypothetical options can be extrapolated. Compensating surplus estimates are put to use as paramount welfare measures associated with characteristics of an environmental resource. In contrast, CVM generally values a composite of non-monetary factors per survey. It is, however, not correct to argue that the contribution of various attributes to the value of an environmental good cannot be estimated separately with CVM (Scarpa 2000). It can be achieved with adequately designed interviews. In particular, CVM practitioners can prepare a number of distinct profiles and present one profile to one respondent at a time, though this is costly in obtaining as many observations as in choice modelling.

Implicit prices for unit changes within attributes

The implicit price means the marginal rate of substitution between a non-monetary attribute and the monetary factor. The implicit price is also referred to as 'part-worth' or the point estimate of WTP. The implicit price is derived holding constant all other parameters except for the parameter of the attribute for which the implicit price is being computed. Mathematically, let one of z_k represent the price factor z_p. Holding $\Delta V_j = 0$ yields:

$$\Delta V_j = \Delta \sum b_k \, z_k^j + \Delta \, b_p \, z_p = 0 \qquad (2)$$

Assume that the level of an attribute changes from a base level to another in terms of environmental quality and levels of k–1 other attributes remain unchanged. The ratio of the particular attribute coefficient to the price coefficient measures the WTP for the hypothetical change of the specific attribute, because utility of the non-monetary attributes is indirectly related to the price factor. The point estimate of WTP with respect to z_k is obtained by:

$$-\frac{dz_p}{dz_k} = -\frac{b_k}{b_p} \qquad (3)$$

For an improvement in environmental quality, b_k is greater than zero. Thus, the ratio is expected to be positive because the sign on b_p, the price parameter, will be negative. Positive ratio values represent attributes that increase utility, whereas negative ratio values (i.e. $b_k < 0$) represent attributes that reduce utility. It is important to note that implicit prices are not appropriate for use as measures of overall welfare created by an environmental change (Morrison *et al*. 1999). The reason is that an implicit price is computed under the assumption that change in utility is equal to zero, as expressed in Equation 2. Compensating surpluses need to be calculated, in order to understand comprehensively the environmental attitudes of stakeholder groups towards a specific environmental option. The calculation of the compensating surplus for an environmental change involves implicit prices of model attributes multiplied by proposed units of changes within each attribute, and the alternative specific constant estimated for the specific option.

Deriving the compensating surplus for environmental improvement

Two types of compensation measures of consumer welfare may be distinguished. 'Compensating variation' is defined as the amount of income that, if given to an individual, would make the individual indifferent in utility terms between the initial and subsequent combinations of the money income and the consumption level of goods. Instead of 'compensating variation', the term 'compensating surplus' is used to describe the welfare change in terms of income, in the situation where individuals are not free to choose the consumption level of goods – for example, public goods such as air quality. In short, compensating surplus measures the difference in utility between two options — namely, the change in income that would make the utility level of an individual indifferent between the initial and subsequent options.

Using indirect utility functions, compensating surplus (CS) for beneficial environmental changes can be defined as in the following equation:

$$\begin{aligned} V_C(E_0, M_0) &= V_C(E_1, M_1) \\ &= V_C(E_1, M_0 - \text{CS}) \\ &= V_N(E_1, M_0) - \text{CS} \end{aligned} \qquad (4)$$

where E indicates a particular environmental good in consideration and M denotes an individual's total money income. The individual can purchase any combination of market goods and services including other environmental goods and services with total money income M, where $M_0 > M_1$. The person's other option is assumed to be an environmental improvement denoted by E, where $E_1 > E_0$. V_C and V_N represent the utility levels of the current situation and alternative state, respectively. From Equation 4, $M_1 = M_0 - CS$, and therefore $CS = M_0 - M_1$. Unlike when deriving implicit prices, the utility level is not required to remain the same. Hence, compensating surplus represents marginal WTP for a change from the current bundle of commodity (E_0, M_0) to (E_1, M_0).

The welfare estimates are obtained by the difference in utility between two options, which is scaled by the marginal utility of income to determine compensating surplus:

$$\begin{aligned} \mathrm{CS} &= -\frac{1}{b_p}(V_C - V_N) \\ &= -\frac{1}{b_p}(\sum b_k z_1^C - \sum b_k z_1^N) \end{aligned} \tag{5}$$

where z_k^1 indicates the kth attribute (except for the price factor). Equation 5 has often been used for estimating compensating surplus for a new level of environmental quality attached to a single site (e.g. Boxall *et al*., 1996; Blamey *et al*., 1998; Morrison *et al*., 1999).

6. SUMMARY

Choice modelling is grounded on the discrete choice model, which can produce a strictly additive utility function. From the estimated utility function, one can ultimately extrapolate consumer surplus for proposed hypothetical environmental changes. For this reason, discrete choice models have recently been applied to value non-market environmental goods such as forests and wetlands around the world in a number of benefit measurement studies.

In designing a choice modelling questionnaire, keeping valid the orthogonality assumption is vital. In the modelling phase, testing for the IIA property is a standard empirical procedure. As well, given the diversity of beliefs, attitudes, interests, knowledge and other factors that might exist in populations, running focus groups sessions is clearly a beneficial step to designing and testing a non-market valuation questionnaire. Focus group sessions are essential particularly for choice modelling practices, considering that the questionnaire format with a number of choice sets is relatively new and complex to potential respondents. Using focus group sessions, a choice modelling practitioner can select design attributes, finalise choice formats, frame the hypothetical market context and identify attitudes that influence participants' responses.

In choice modelling applications to environmental resources, environmental quality as well as monetary factors are included as attributes of the options in a choice set. Thus, choice modelling allows one to obtain compensating surplus estimates so that one can account for the welfare change generated by a bundle of changes in environmental attributes. It is also possible to determine the relative importance of these attributes to people in making their choices.

In choice modelling practice, respondents are offered hypothetical combinations of attributes associated with a set of scenarios. By downplaying the payment factor, choice modelling is much more aptly able to estimate preferences with the effect of reducing the payment vehicle bias relative to CVM. The mechanical framework of a discrete choice model allows researchers to disaggregate the utility function attached to a particular good, which is a compelling advantage of choice modelling over CVM. A choice modelling exercise can produce point estimates of WTP for changes in the attribute levels varied in the choice sets as well as compensating surplus estimates for a conceptually unlimited number of underlying scenarios. Choice modelling can avoid problems posed with contingent ranking and contingent rating. These latter methods face many critics because of theoretical problems such as lack of error theory, and measurement bias that occurs because of interpersonal comparison of utility.

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APPENDIX A: THE ORTHOGONAL FRACTIONAL FACTORIAL DESIGN

The orthogonal fractional factorial design can be obtained by the systematic draw from the factorial of possible combinations. The requirement is satisfied when each level of one factor occurs with each level of another factor with proportional frequencies (Green 1974). Rolfe and Bennett (1996) recommended allocating consistent numbers of levels across attributes if possible for the simplicity of a symmetrical orthogonal array. However, nothing is technically or practically wrong with varying numbers of levels between attributes, which leads to an asymmetrical orthogonal array, as long as each level will occur an equal number of times within each attribute, in each individual choice set and throughout the entire set of alternatives.

Louviere (1988), Adamowicz *et al*. (1994) and Bennett (1999) emphasised that separate choice sets of alternatives should be treated independently. They suggested that this requirement be achieved by adding the 'no-change' option – i.e. the 'current situation' option – to each and every choice set. Each choice set is then evaluated without regard to previously presented choice sets. The provision of the 'current situation' option allows respondents to state that they would prefer not to purchase any of hypothetical alternatives presented in the choice set. Carson *et al*. (1994) called for caution about the possibility that respondents may use the 'no-purchase' option as a means to avoid making difficult decisions. In that case, adding the 'no-change' option to each choice set can adversely influence on the value estimates.

APPENDIX B: MATHEMATICAL FORMULATION OF CHOICE MODELLING – THE DISCRETE CHOICE MODEL

The discrete choice model is usually called the conditional logit model, which McFadden (1974) derived from random utility. The conditional logit model concerns the effects of choice-specific attributes on the determinants of choice probabilities. To formulate the conditional logit model, consider the case of J mutually exclusive and collectively exhaustive options labelled arbitrarily, where the numberings cannot be taken to indicate order or any magnitude. Respondents will be making comparisons between options with the utility of the jth option. The indirect utility of the jth option can be represented by:

$$V_j = V(z_k^j) + \varepsilon_j \tag{6}$$

where $V(z_k^j)$ is the systematic component of utility and ε_j is a random unobservable component. The systematic component is assumed to be the same for all observations while the random component is unique to each consumer. Assuming $E(\varepsilon_j) = 0$, the probability P_j that the jth outcome is observed is:

$$\text{Prob}\,[V(z_k^j) > V(z_k^{j'})] \quad j = 1,2,\cdots,J \text{ for all } j' \neq j \tag{7}$$

The systematic component $V(z_k^j)$ can be expressed as the sum of combinations of attributes given by:

$$\begin{aligned} V(z_k^j) &= b_0 + b_1 z_1^j + b_2\, z_2^j + \cdots + b_K\, z_K^j \\ &= \sum_{k=1}^{K} b_k\, z_k^j \equiv bZ \end{aligned} \tag{8}$$

where z_k^j refers to the kth attribute of the jth option, and one of z_k represents the price, b_k is the weight or coefficient associated with an independent variable z_k, and bZ is the linear combination of attributes with a single parameter vector b. It is notable that the same attributes appear in the utility function for every choice with varying levels within each attribute. This is not a requirement of conditional logit models, but a common feature of most choice modelling applications.

The probability of an outcome in Equation 7 is a linear function of independent variables. The problem with the linear probability model specification is that bZ is used to approximate a probability P_j that is limited between from 0 to 1, whereas bZ is not so constrained. That is, P_j is non-linearly related to z_k as well as to the b_k. This means that ordinary least square procedures cannot be used to estimate the parameters. To solve this problem, Aldrich and Nelson (1984) have demonstrated derivation of non-linear probability specifications. To begin with, it is necessary to take the logistic function as a non-linear transformation function of Equation 7:

$$P_j = \text{Prob}\,[y_j = 1 \mid V(z_k^j)] = \exp(bZ) \Big/ \sum_{j=1}^{J} \exp(bZ) \qquad (9)$$

where y_j is the index of the choice made given that the random utility of the choice is $V(z_k^j)$. Next, the upper bound P_j can be estimated by taking the ratio $P_j / P^{j'}$. The ratio must be positive, and since P_j and $P^{j'}$ are constrained between 0 to 1, the ratio has no upper bound. The lower boundary of zero can be eliminated by taking the natural logarithm, In (P_j/ Pj'), the value of which can be any real number from negative to positive infinity:

$$L_j = \ln\left(\frac{P_j}{P_{j'}}\right) = V(z_k^j) = b_0 + b_1 z_1^j + \cdots + b_K\, z_K^j \qquad (10)$$

The ultimate goal of applying choice modelling is to estimate the coefficients (i.e. b_k) from the logit model. The logit model represented by Equation 10 defines the logarithm of probabilities that a particular choice will be made. Yet the coefficients estimated also directly relate to the utility (Rolfe and Bennett 1996). The higher the utility of a particular attribute level in Option j, the higher the odds ratio – that is, the higher the probability that a respondent will choose the particular option. Again, each coefficient estimated represents the marginal contribution of an attribute to overall utility.

Logit models are estimated by the maximum likelihood technique. This can be achieved by using a non-linear maximisation program such as Limdep. The maximum likelihood estimation procedure has a number of desirable statistical properties. Among those, two aspects are notable (Pindyck and Rubinfeld 1991). First, parameter estimators are asymptotically consistent and efficient. Second, all parameter estimators are known to be normally distributed, so that the analog of the regression t-test can be applied. One can then apply the likelihood ratio test to determine whether a logit model provides an appropriate model specification.

APPENDIX C: TESTING FOR ‘INDEPENDENCE OF IRRELEVANT ALTERNATIVES’

When an independence of irrelevant alternatives (IIA) violation is found for a conditional logit model, Morrison *et al*. (1999) suggested including socio-economic characteristics, attitudinal variables or questionnaire evaluation variables in the model. For the conditional logit model, these variables can be included in one or both of two ways. The first is through interactions with the alternative specific constants. These interactions reflect the effect of these variables on the choice probability that a respondent will choose either Option 2 or Option 3. The second is by interactions with the attributes in the choice sets. These interactions indicate that the non-attribute variables can modify the effects of attributes on the choice probability of an option. The interaction effects between non-attributes (e.g. socio-economic characteristics of individuals) and choice specific dummy variables or between non-attributes and attributes are not restricted by the orthogonal design.

If a conditional logit model containing interaction terms of non-attribute variables is found to violate the IIA property, it becomes necessary to estimate a more complex model that relaxes part of the IIA assumption. An example of this type of model is the nested logit model. The IIA assumption in the nested logit model is relaxed because the options are divided into subgroups across which the variance is allowed to differ while maintaining homoscedasticity within the groups (Greene 1997). However, it is still necessary to test a nested logit model for the IIA property because the IIA violations can occur due to the presence of close substitutes within the same branch in a choice set.

In non-nested logit models, all elemental nodes are connected to the root of the tree as in Figure 1. In nested logit models, construct nodes are introduced. Assume there are three choices in each choice set. Option 1 is the 'no-change' option and appears in every choice set. Combinations of attribute levels for Options 2 and 3 vary across choice sets. Option 1 is labelled as the 'current situation', whereas Options 2 and 3 are labelled as 'new options'. The nesting occurs when an individual chooses first, for example between Option 1 (current situation) and Option 2 or 3 (new options), and then, conditional on not choosing Option 1, chooses between Option 2 and Option 3. A tree relevant to this situation can be specified as in Figure 2.

Various methods of detecting violations of the IIA property have been proposed (Ben-Akiva and Lerman 1985; Zhang and Hoffman 1993). A Hausman and McFadden (1984) test is often used. To carry out the test, a specific option throughout choice sets is excluded. A logit model with the restricted set of options but with the same model specification as the model with all choices included is then estimated. One can next check whether there is any change between the two models, and evaluate whether the new coefficients are sufficiently similar to the original ones, so as to satisfy the IIA property. The test statistic for checking the IIA assumption is distributed as a chi-square variable. This type of test can be carried out using the Limdep statistical package.

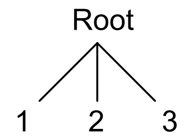

Figure 1. Tree diagram for a non-nested logit model (Model 1)

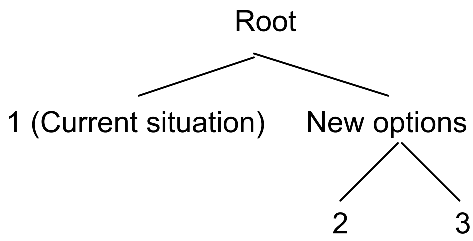

Figure 2. Tree diagram for a two-level nested logit model (Model 2)

Another test proposed by Hausman and McFadden (1984) is applicable to nested logit models, which allows the independence property to be tested directly. For example, IIA violations occur if Options 2 and 3 in Figure 2 have correlated unobservable factors.

In Figure 2, 'new options' is a construct node with parameter θ. This nested logit model assumes that the correlation between the errors of Options 2 and 3 is given by $(1 - \theta^2)$. If the hypothesis that $\theta = 1$ cannot be rejected, which can be tested using a likelihood ratio test comparing Models 1 and 2, then it can be concluded that Model 2 does not violate the IIA assumption. That is, testing of the IIA property is equivalent to determining whether the estimated value of θ is significantly different from 1.

There are other methods to test for the IIA assumption. Rolfe and Bennett (1996) suggested checking if a change in one attribute produces shifts in choice greater than expected. Adamowicz *et al*. (1994) noted that the cross effects should equal zero if the attributes are strictly independent, apart from the belief that the attributes of one option could influence the utility of another option. Morrison *et al*. (1999) introduced the universal logit model, which was also proposed by McFadden *et al*. (1977), to detect violations of the IIA assumption. In estimating a universal logit model, called a 'mother logit model', the attributes of one option are entered into the utility function of a second option, and then the attributes of the second option into the utility function of the first option. If the model is found to be the more accurate model, the utility of one option can be considered to depend on the utility of other options, thus violating the IIA property.